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Predictive Power of Aggregate Short Interest[†]

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Abstract: The short sale of a stock is motivated by financial profits an investor expects to gain from declining stock prices. Short interest, defined as the proportion of shares shorted to all outstanding shares for a given stock, represents the collective expectations of short sellers. While the variation in short interest at the firm level may be dominated by firm-specific expectations, the variation in an aggregate measure of short interest across a broad sample of stocks most likely reflects changing expectations of macroeconomic conditions. With this motivation, this paper examines the relationship between lagged aggregate short interest and cyclical changes in GDP using quarterly US data from 1973 to 2013. The results strongly suggest that lagged aggregate short interest is a statistically significant regressor in explaining cyclical changes in GDP at up to a 4 quarter lag. Moreover, these results do not change with the addition of control variables and are robust to the use of different filters to decompose the growth trend from the cyclical component of GDP.

Keywords: Short Interest, Business Cycle Forecasting, Trend-Cycle Decomposition

JEL Classification: E32, E37, G17

[†] This is a working paper and the date shown is the date of last revision.

1 Introduction

Short interest for a given stock is simply the number of shares short sold in proportion to the total number of shares outstanding for the stock. Investors, to short sell, borrow shares of a stock and sell them on the market in the hopes of paying back the shares they borrow by purchasing them at a lower price later. They engage in this type of a short sale because the future price they expect for the stock is lower than the current price. After all, if investors expect a zero probability of a future decrease in the price of a stock, these investors will not engage in the short sales. When investors, in fact, engage in short sales, it is because they have a non-zero probability of a future decrease in the price of the stock they short sell, based on their valuation-based or momentum-based expectations. When these expectations are aggregated for a broad sample of stocks, the resulting measure reflects how shorted the stock market is overall. Through aggregation, firm-specific expectations no longer play as important a role in the variation of the short interest measure. Rather, the variation in the aggregate short interest reflects the changing expectations of macroeconomic conditions. More specifically, an increase or a decrease in the aggregate short interest is most likely based on short sellers' collective expectations of the macroeconomic conditions that affect the expected probability of a market wide decline in stock prices.

Certainly there are countless macroeconomic conditions an economy faces. Examples include global commodity prices, unemployment levels and exchange rates. It is no stretch to claim that these macroeconomic conditions are important determinants of economic growth. Imagine now that investors expect the macroeconomic conditions to turn unfavorably for economic growth in the near future. If stock prices are fairly accurate representations of the respective firms' discounted lifetime cash flow, investors have a profit motive to short sell stocks when changes in economic growth are expected to squeeze the respective firms' cash flow in the near future. If, however, investors expect the macroeconomic conditions to turn unfavorably for economic growth in the distant future, the profit motive to short sell may still exist but most certainly is reduced because of the discount rate that puts little weight on the expected cash flows in the distant future. Any gradual change in the long term that affects a firm's discounted lifetime cash flow is not as strong a motivation for investors to engage in short sales as an imminent change. Then, macroeconomic conditions that affect economic growth in the long term are not what investors consider in their decision to short sell. Rather, it is the macroeconomic conditions that affect the short term economic growth. This means that the trend of GDP which reflects the long term macroeconomic conditions does not interest short sellers much. A simple correlation verifies this. Changes in quarterly GDP has no significant correlation with the aggregate short interest because the growth trend of GDP adds information that short sellers do not consider. Once

the trend is removed, however, the cyclical component of GDP which reflects the short term macroeconomic conditions reveals a significant correlation with the aggregate short interest.

Naturally the paper attempts to establish a meaningful relationship between an aggregate measure of short interest and cyclical changes in GDP. Then, trend-cycle decomposition is required to remove the growth trend from GDP. To be sure, suppressing the growth trend with simple log differencing does not fundamentally remove the trend from GDP. Again, a simple correlation verifies this. The log differenced GDP does not have any significant correlation with the aggregate short interest. In business cycle research, a common filter for trend-cycle decomposition is the Hodrick-Prescott (HP) filter, popularized by Hodrick and Prescott (1997). Harvey and Jaegar (1993) notes that the HP filter is a widely used detrending technique. Ravn and Uhlig (2002) cites numerous empirical papers that have applied the HP filter to real data such as Backus and Kehoe (1992), Blackburn and Ravn (1992), Brandner and Neusser (1992), Danthine and Donaldson (1993), Danthine and Giardin (1989), Fiorito and Kollintzas (1994) and Kydland and Prescott (1990). Furthermore, Ravn and Uhlig (2002) claims that the use of the HP filter has been subject to heavy criticism but will remain one of the standard methods for detrending. To ensure that the results in this paper are not spurious, multiple filters are used to add robustness.

A meaningful relationship between an aggregate measure of short interest and cyclical changes in GDP, once established, is an invaluable asset. It allows for the extrapolation of short sellers' collective expectations of future macroeconomic conditions. Consider an economy in a bust. It experiences high unemployment rates, strong investments and a negative output growth. As a result of the latest bust, generally cited the Great Recession in the United States, approximately 3.3% of real GDP was lost. Unfortunately, as in any recession, the burden of the loss in real GDP is not shared with everyone but falls, for example, on those who lose their livelihoods altogether. Economic busts for these individuals are harsh, ruthless and even devastating. The effect of an economic bust is not only socially undesirable but also quite persistent. It is for these reasons that central banks employ monetary policies and governments use fiscal policies to alleviate all the hardships an economic bust brings in a more expeditious manner. In fact, the Federal Reserve lowered its policy rate to its minimum lower bound and engaged in open market operations at an unprecedented scope to bring a quick end to the Great Recession. The US government also put in place the American Recovery and Reinvestment Act of 2009, a fiscal stimulus package which the Congressional Budget Office estimates to be worth 831 billion dollars. Although recessions are realized in hindsight, if the Great Recession could have been realized earlier, these measures could have come sooner. The potential to gauge sophisticated investors' expectations of future economic outlook may reduce the recognition lags associated with recessions.

2 Literature Review

There are countless papers published on the topic of short selling. However, only few that are instrumental to this paper are discussed. It is only natural to wonder who is engaging in short sales and why this information may be useful. Hanson and Sundaram (2013) notes that equity short sellers are typically sophisticated investors. This is backed by Ben-David, Franzoni and Moussawi (2012) as well as Boehmer, Jones and Zhang (2013). Both indicate that hedge funds account for most of the short interest in the US. This is not at all surprising. Unlike traditional investments in stocks from which investors can at most lose the principal, short selling can, in theory, have unlimited liability for the investors. The short sellers are putting their money where their mouths are by taking on such a liability. It is also natural to wonder if there is any distortion in the short interest information. Short selling may have supply constraints. Investors who want to short sell may not be able to because they cannot find others that are willing to lend the shares to them. This type of constraint may become a source of endogeneity. Asquith, Pathak and Ritter (2004) concludes that short selling constraints are unlikely and that those who want to short sell do not face supply constraints. At the firm level, short interest is shown to have predictability for negative abnormal returns in Boehmer, Huszar and Jordan (2010). This is not all. Also at the firm level, Curtis and Fargher (2013) finds empirical evidence that short sellers primarily undertake valuation-based strategies instead of momentum-based strategies. All of these papers reiterate the potential value in the short interest variable.

The firm level short interest data have been aggregated previously to investigate the informational content in the aggregate measure. Lamont and Stein (2004) uses Nasdaq short interest data from 1995 to 2002 and concludes that the total short interest moves countercyclically to the stock market based on the negative correlation between the Nasdaq index and their short interest ratio. The negative correlation between the total market capitalization and the aggregate short interest is reproduced in this paper as well not just for the dotcom era but for the entire 40 year period from 1973 to 2013, consistent with the results of Lamont and Stein (2004). There is no dispute that the aggregate measure of short interest fell during the dotcom era. However, based on this evidence, Lamont and Stein (2004) implies a conclusion that short sellers at the aggregate level do not seem to correct mispricings. This seems to be the case for the dotcom era. After all, it is indeed correct that the dotcom bubble was a case of mispricing. It is also correct that the aggregate short interest was reduced during the dotcom bubble. This result is in line with Griffin, Harris, Shu and Topaloglu (2011) which finds that sophisticated investors, especially hedge funds did not move against clear mispricings during the dotcom era. However, the negative correlation in Lamont and Stein (2004) alone cannot be used to reasonably justify the general conclusion that short sellers do not correct mispricings at the aggregate

level. If history is any indication, an increase in the index value or the total market capitalization is, in general, a reflection of the increase in aggregate firm value, not a case of mispricing. Hence, the negative correlation between the aggregate short interest and the stock market value is not at all surprising and is most likely not enough evidence to generalize that short sellers do not seem to correct aggregate mispricing for all periods. The conclusion of Stein and Lamont (2004) is not inconsistent with the premise or the empirical findings of this paper.

3 Data

3.1 Source of Data

Short interest data in this paper are from the `SHORTINT` variable of Compustat. The data reflect the short positions held on the 15th business day of each month for each stock. This is available without delay. Stock price, total shares outstanding and value-weighted stock market return data are respectively from the `PRC`, `SHROUT` and `VWRETD` variables of CRSP. The data on stock price and total shares outstanding are daily data for each stock. However, the value-weighted stock market return data reflect monthly returns, including all distributions, on a value-weighted market portfolio excluding American Depositary Receipts (ADRs). This is reported at the end of each month and available without delay. GDP data are quarterly data and are from the `GDPMC1` series of the US Bureau of Economic Analysis. This is released with a considerable delay. The first estimates of GDP are available approximately a month after the end of each quarter. The second estimates of GDP are available approximately two months after the end of each quarter. The third estimates of GDP are available approximately three months after the end of each quarter. The federal funds rate and yield on 10 year US treasury bonds are respectively from the `FF_0` and `TCMNOM_Y10` series of the Federal Reserve. These are monthly data reported at the end of each month. The price index data used to compute inflation are from the `CPIAUCSL` series of the Federal Reserve Bank of St. Louis. The data reflect the price index values at the beginning of each month. Finally, the recession dates used in this paper come from the National Bureau of Economic Research (NBER).

All of the data are converted to quarterly data. In essence, the data on the 15th business day of the third, sixth, ninth and twelfth months represent respective quarter's data for short interest. The price data and the shares outstanding data are matched with the short interest data for each stock for each quarter. Index values are created for the monthly value-weighted market returns. They are then converted to the quarterly value-weighted market returns by taking the percentage difference between the index values for each quarter.

The data at the end of the third, sixth, ninth and twelfth months represent respective quarter’s data for the federal funds rate and yield on 10 year US treasury bonds. Inflation is manually computed by taking the percentage difference between the price index values for each quarter. The monthly recession dates from the NBER are converted to quarterly dates by assigning the first three months of a year as the first quarter, the next three months of a year as the second quarter, the next three months of a year as the third quarter and the last three months of a year as the fourth quarter.

3.2 Construction of Aggregate Short Interest

In order to construct a time series for the value-weighted aggregate short interest, the number of shares shorted for each stock, the total number of shares outstanding for each stock and the proportion of each stock’s capitalization to the total market capitalization are required. Unfortunately, the **SHORTINT** series from Compustat reports the number of shares shorted for each stock without the corresponding price and total shares outstanding data. The missing information is provided by the **PRC** and **SHROUT** series from CRSP. As Compustat identifies each stock with **gvkey** and CRSP with **permno**, **lpermno** from the linking table of CRSP/Compustat Merged Database is used to convert **permno** to **gvkey** for CRSP data. Compustat data and CRSP data are then merged by **gvkey**, excluding observations that do not exist in both data sets.

Once the two data sets are merged, the number of shares shorted for each stock is divided by the total number of shares outstanding to represent the proportion shorted for each time period. Each stock’s market capitalization is calculated for each time period and then divided by the sum of all market capitalizations for each time period to arrive at the value weights. The weight multiplied by the proportion of short interest represents the value-weighted short interest for each stock for each time period. Adding across all stocks for each time period results in a time series of aggregate value-weighted short interest, referred to as the aggregate short interest throughout the paper.

3.3 Overview of Data

Summary statistics for the main variables used in this paper are conveniently located in Table 1. The first four variables in the table are cyclical components of the change in quarterly GDP. The growth trend in quarterly GDP is removed by the use of four different filters. In order to avoid spurious regressions, the GDP data passed through various trend-cycle decomposition filters are tested for stationarity. The Dickey-Fuller test for stationarity is run on the quarterly GDP series passed through the Hodrick-Prescott (HP) filter and Butterworth (BW) filter. Both of the resulting series are found to be stationary at the 5% significance

level. However, the Dickey-Fuller test for the quarterly GDP series passed through Christiano-Fitzgerald (CF) filter and Baxter-King (BK) filter indicate that the resulting series are not stationary at the 5% level. The Phillips-Perron test, an alternative test for stationarity, indicates that the series passed through the CF filter and BK filter are stationary at the 5% level.

The next four variables in the table are the aggregate short interest measures at various lags. The first aggregate short interest measure is lagged by one quarter. The second measure is lagged by two quarters. The third measure is lagged by three quarters. Finally, the fourth measure is lagged by four quarters. All four of these time series are also tested for stationarity using the Dickey-Fuller test. They are all found to be stationary at the 5% level. The federal funds rate and US treasury 10 year bond yield, used in this paper as control variables, are not stationary at the 5% level. Both exhibit a downward trend over time. The stock market return and inflation, used in the paper also as control variables, are stationary at the 5% level. The last two variables in the table are binary variables. The first binary variable indicates with one when cyclical changes in GDP from one quarter to the next are negative and zero otherwise. The second binary variable indicates with one if there is a recession as defined by the NBER and zero otherwise.

Correlations between the variables used in this paper are provided in Table 2. It is evident that there is no significant correlation between the US treasury 10 year bond yield and cyclical changes in GDP. Also evident is the lack of significant correlation between stock market return and cyclical changes in GDP. A quick check on the signs shows that the correlations are in fact sensible. The aggregate short interest measures at one and two quarter lags are negatively correlated with cyclical changes in GDP. The implication is clear. A rise in the aggregate short interest measures is associated with a decline in cyclical GDP a quarter to two later. The federal funds rate has a positive and significant correlation with cyclical changes in GDP. This, also, is clear. Tightening of monetary policy is often the policy response to positive cyclical changes in GDP. Furthermore, the positive and significant correlation between inflation and cyclical changes in GDP is obvious. In general, GDP increases beyond trend is accompanied by rising inflation. Although discussed further in the results section, it is worthwhile to note the significant correlation between inflation and the federal funds rate.

A visual inspection is often useful for an intuitive understanding of the variables. Figure 1 shows the number of firms whose short interest data are reported by Compustat. Note that the obvious jump in the number of firms covered in 2003 is the result of extended coverage in the data set. Nasdaq data became available in 2003 in Compustat. In 1978, the number of firms listed on the AMEX and NYSE was 2,585. This number changed to 2,576 in 1988 and to 3,380 in 1998. The number of firms listed on the AMEX,

NYSE and Nasdaq was 5,472 in 2008. The trend is clear. The number of firms whose short interest data is reported is getting more representative of the overall stock market.

	1978	1988	1998	2008
AMEX	1,004	895	711	486
NYSE	1,581	1,681	2,669	2,449
Nasdaq	-	-	-	3,023
Total	2,585	2,576	3,380	5,472

Source: World Federation of Exchanges

Figure 2 shows the value-weighted aggregate short interest across these firms. It is evident from this figure that there is a run-up in the measure before and during the recessionary periods. As it turns out, the magnitude of the run-up in the aggregate short interest for each recession roughly corresponds to the severity of the recession.

	Δ Real GDP (%)
1973Q3 - 1975Q1	-2.4
1980Q1 - 1980Q3	-2.2
1981Q3 - 1982Q4	-2.5
1990Q3 - 1991Q1	-0.6
2001Q1 - 2001Q4	-0.1
2007Q4 - 2009Q2	-3.3

Source: US Bureau of Economic Analysis

The quarterly GDP series passed through the HP filter is plotted in Figure 3. As expected, the cyclical component of GDP obtained from the HP filter indeed shows sharp decline during recessions.

4 Results

4.1 Model Selection

The main hypothesis of this paper is that the variation of the aggregate short interest is driven by sophisticated investors' collective expectations of future outlook on economic growth. In order to establish a meaningful association between the aggregate short interest and cyclical changes in GDP, Table 3 reports the

results of regressions that include short interest together with all the control variables. As expected from the correlation table, stock market return does not have statistically significant explanatory power for cyclical changes in GDP. This together with the low correlation between the two variables lends empirical support for eliminating stock market return as one of the regressors. However, the significant correlation between inflation and cyclical changes in GDP from the correlation table does not translate to statistical significance for inflation as a regressor. Further examination reveals that the reason for the lack of significance in inflation lies in its significant correlation with the federal funds rate. It is no surprise that the policy rate that aims to control inflation is highly correlated with inflation. Note also that the correlation between US treasury 10 year bond yield and cyclical changes in GDP is shown to be insignificant in the correlation table. However, all the regressions in Table 3 show significance for the bond yield. This inconsistency is addressed in Table 4 where the joint significance of the federal funds rate and the bond yield is apparent. The regression results reported in Table 4 confirm that eliminating the federal funds rate or inflation allows the remaining regressor to retain significant explanatory power in the resulting regressions. The higher goodness of fit for the regression with the federal funds rate remaining in the model lends justification for removing inflation.

4.2 Main Results

With the stock market return and inflation removed, the remaining federal funds rate and US treasury 10 year bond yield serve as controls. Table 5 reports the results of regressions designed to examine the predictive power of the aggregate short interest over and beyond the explanatory power of the controls in place. The first regression with the aggregate short interest at one quarter lag displays statistical significance on all regressors at the 5% level. The result continues to be consistent with the aggregate short interest at three quarter lags. The aggregate short interest finally loses significance at the 5% level at four quarter lags. Note that all four regressions result in coefficients of the same sign. As expected, the aggregate short interest has a negative sign on its coefficient at all lags. The federal funds rate has a positive sign on its coefficient in all four regressions while the US treasury 10 year bond yield has a negative sign, consistent with the previous regression results. These regressions suggest that the aggregate short interest at the lag of up to three quarters has significant explanatory power for cyclical changes in GDP over and beyond what the federal funds rate and US treasury 10 year bond yield can explain.

While the results suggest that the aggregate short interest is indeed predictive of cyclical changes in GDP, perhaps the more practical feature is the predictive power to determine whether impending cyclical changes in GDP are negative or not. After all, the sign of the change is arguably more important than the

magnitude. To see the power that lies in the aggregate short interest to predict negative cyclical changes in GDP, a binary variable is created to indicate with one when cyclical changes in GDP are negative. Table 6 reports the results of logit regressions of this binary variable on the aggregate short interest at various lags and the control variables. The aggregate short interest shows the ability to predict negative cyclical changes in GDP. This ability is significant even at the lag of four quarters at the 5% level.

The positive sign on the coefficient of the aggregate short interest in Table 6 indicates that an increase in the aggregate short interest today leads to an increase in the probability of negative cyclical changes in GDP in the upcoming quarters. In addition, the federal funds rate has a negative coefficient and the US treasury 10 year bond yield has a positive coefficient in all the regressions in Table 6. The negative sign on the federal funds rate most likely reflects the fact that the Federal Reserve, in general, decides to lower policy rate in the face of recessions. Conversely, the positive sign on the bond yield likely reflects the excess demand for funds due to government's deficit financing during recessions. Knowing the government has to fulfill its own budget constraint, deficit financing drives down the price of bonds and puts an upward pressure on the bond yields. Although not shown, probit regressions of the same form lead to virtually identical results.

Extending the analysis further, Table 7 reports the results of logit regressions designed to examine the power of the aggregate short interest to predict recessions as defined by the NBER. To do so, a binary variable is created that indicates with one if there is a recession as defined by the NBER and zero otherwise. The logit regressions of this binary variable on the aggregate short interest and the aggregate short interest at one quarter lag show weak results. However, recall that quarterly GDP data are reported with a significant delay. Even the advanced estimates of quarterly GDP are available only a full month after the end of each quarter from the US Bureau of Economic Analysis. The firm level short interest data, on the other hand, are reported without delay around the 15th business day of each month. The first quarter short interest data, for example, are released on the 15th business day of March. When the first quarter GDP data are matched with the first quarter short interest data, the pair may appear contemporaneous but in actuality the short interest data precede the GDP data by a considerable amount.

Despite the weak results from the logit regressions, the significance on the coefficient of aggregate short interest with no lag still indicates some predictive power for recessions as they are not contemporaneously available. Moreover, the NBER does not always recognize the end of a recession as soon as the business activity in the economy picks up after a recession. The NBER applies its judgment in its decision to determine when a recession begins and when it ends. This arbitrary nature combined with too few recessions in the sample may be contributing to the lack of significance on the lagged aggregate short interest.

5 Robustness

Internal consistency is examined to see if additional tests produce sensible and consistent results. The paper has found empirical evidence for predictive power in the aggregate short interest. This implies that short sellers have the ability to vary the aggregate short interest in anticipation of cyclical changes in GDP. It may be the case that those who engage in short sales are uniquely informed or are inherently better equipped to interpret and forecast using the same set of information available to the general public. Regardless of the reason, it is logical to suspect that the ability to forecast should deteriorate as they form their expectations farther into the future. The results in Table 8 show precisely this. As the aggregate short interest with increasing lags are examined, the slow and consistent decline in t statistics is apparent. There is no erratic pattern in the significance of the aggregate short interest with increasing lags.

Much of the paper has made use of cyclical changes in GDP. The quarterly GDP data are passed through the HP filter to generate the GDP series that has growth components removed. In order to ensure that the results found in the paper are not unique to the use of the HP filter, three separate regressions that use different filters are reported in Table 9. The aggregate short interest at one quarter lag retains its statistical significance at the 5% level with BW, CF and BK filters. It is quite clear that the results are robust to the use of different methods of trend-cycle decomposition and that the main results do not change.

6 Conclusion

The aggregate short interest is shown to have the power to predict negative cyclical changes in GDP at up to four quarters earlier. Furthermore, the aggregate short interest is shown to be a statistically significant variable in explaining the variation of cyclical changes in GDP at up to three quarters earlier. These results withstand the use of the federal funds rate and US treasury 10 year bond yield as controls and are robust to the use of different methods of trend-cycle decomposition. It seems that the collective group of investors who engage in short sales is typically able to anticipate a market wide decline in stock prices. The results indicate that the variation in the aggregate short interest is likely driven by the short sellers' expectations of macroeconomic conditions. The relationship between the aggregate short interest and cyclical changes in GDP, established in this paper, allows for the extrapolation of short sellers' collective expectations of future macroeconomic conditions. These expectations provide a valuable insight into their prediction of the direction and variation of future economic growth.

Table 1: Summary Statistics

The quarterly US GDP time series from 1973:1 to 2013:3 is decomposed into its trend and cyclical component using the Hodrick-Prescott filter, Butterworth filter, Christiano-Fitzgerald filter and Baxter-King filter. The first four GDP variables represent the cyclical components of the quarterly change in GDP obtained using these four filters. The stock level short interest data are aggregated across a broad sample of stocks using value-weights based on market capitalizations for each time period. The next four short interest variables found in this table are the quarterly value-weighted aggregate short interest at various lags. The federal funds rate and treasury 10-year yield are provided by the Federal Reserve for each quarter and used without modification. The stock market return is the monthly value-weighted return including distributions calculated by Compustat converted to quarterly return. The inflation data are computed for each quarter from the consumer price index. The last two variables found in this table are binary variables, one to indicate a negative cyclical change in GDP and the other to indicate a recession as defined by the NBER.

	Count	Mean	σ^2	σ	Min	Max
Δ GDP with Hodrick-Prescott	163	-2.50e-09	1.022193	1.011036	-3.01784	2.412053
Δ GDP with Butterworth	163	-2.09e-09	.7078322	.8413277	-2.703063	2.126706
Δ GDP with Christiano-Fitzgerald	163	.0036097	.9336206	.9662404	-2.953069	2.182555
Δ GDP with Baxter-King	139	-.0161492	.9283476	.963508	-2.941692	2.338134
Short Interest [‡]	163	3.268848	1.100399	1.048999	1.679815	7.628001
Short Interest ^{‡‡}	162	3.276032	1.09877	1.048222	1.679815	7.628001
Short Interest ^{‡‡‡}	161	3.284014	1.095251	1.046542	1.679815	7.628001
Short Interest ^{‡‡‡‡}	160	3.291432	1.093224	1.045574	1.679815	7.628001
Federal Funds Rate	163	5.790613	15.54146	3.942266	.07	19.1
Treasury 10-Year	163	6.893436	8.683892	2.946844	1.62	15.32
Stock Market Return	163	2.83053	80.8056	8.989194	-24.54108	24.4761
Inflation	163	1.055319	.8126101	.9014489	-3.416988	4.161248
$-\Delta$ GDP with Hodrick-Prescott	163	.4846626	.2513065	.5013048	0	1
Indicator for NBER Recession	163	.1779141	.1471635	.383619	0	1

[‡] The number of [‡] indicates the number of lags for aggregate short interest.

Table 2: Correlation Table

The statistical significance for correlations is indicated by * for significance at the 5% level, ** for significance at the 1% level and *** for significance at the 0.1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Δ GDP with Hodrick-Prescott	1						
(2) Short Interest [‡]	-0.237**	1					
(3) Short Interest ^{‡‡}	-0.237**	0.858***	1				
(4) Federal Funds Rate	0.191*	0.299***	0.283***	1			
(5) Treasury 10-Year	0.000151	0.369***	0.366***	0.894***	1		
(6) Stock Market Return	-0.0319	0.167*	0.106	-0.0450	0.0310	1	
(7) Inflation	0.226**	0.204**	0.224**	0.610***	0.476***	-0.0568	1

[‡] The number of ‡ indicates the number of lags for aggregate short interest.

Table 3: Effects of Aggregate Short Interest on Cyclical Changes in GDP with Controls

Each column in this table reports the results of OLS regressions using cyclical changes in GDP as the dependent variable. The first regression indicates lack of statistical significance on the stock market return and inflation. The second regression removes the inflation to see if the stock market return becomes a significant regressor. The third regression instead removes the stock market return to see if the inflation becomes a significant regressor. The fourth regression shows consistent results as the first regression using the second quarter lag of the aggregate short interest instead of the first quarter lag. The statistical significance for coefficients is indicated by * for significance at the 5% level, ** for significance at the 1% level and *** for significance at the 0.1% level and t statistics are in parentheses.

	(1) Δ GDP with Hodrick-Prescott	(2) Δ GDP with Hodrick-Prescott	(3) Δ GDP with Hodrick-Prescott	(4) Δ GDP with Hodrick-Prescott
Short Interest [‡]	-0.253*** (-3.49)	-0.247*** (-3.49)	-0.240** (-3.31)	
Short Interest ^{‡‡}				-0.237** (-3.26)
Federal Funds Rate	0.215*** (4.60)	0.239*** (6.03)	0.209*** (4.24)	0.206*** (4.30)
Treasury 10-Year	-0.242*** (-4.32)	-0.254*** (-4.72)	-0.234*** (-4.04)	-0.235*** (-3.99)
Stock Market Return	0.00940 (1.01)	0.00930 (0.96)		0.00743 (0.78)
Inflation	0.113 (0.86)		0.112 (0.80)	0.126 (0.96)
Constant	1.097*** (4.02)	1.145*** (4.25)	1.069*** (3.79)	1.043*** (3.94)
Observations	162	162	162	161

[‡] The number of ‡ indicates the number of lags for aggregate short interest.

Table 4: Goodness of Fit with Different Controls

The federal funds rate and inflation are separately and significantly correlated with cyclical changes in GDP. However, as the federal funds rate and inflation are very highly correlated themselves, including both in the regression model does not add much incremental benefit. Each column of this table reports the results of OLS regressions using cyclical changes in GDP as the dependent variable. The first regression shows the goodness of fit for the model that excludes the inflation. The second regression shows the goodness of fit for the model that excludes the federal funds rate. The statistical significance for coefficients is indicated by * for significance at the 5% level, ** for significance at the 1% level and *** for significance at the 0.1% level and t statistics are in parentheses.

	(1) Δ GDP with Hodrick-Prescott	(2) Δ GDP with Hodrick-Prescott
Short Interest [‡]	-0.233** (-3.32)	-0.274*** (-3.91)
Treasury 10-Year	-0.247*** (-4.49)	-0.0121 (-0.37)
Federal Funds Rate	0.232*** (5.80)	
Inflation		0.330*** (3.50)
Constant	1.118*** (4.07)	0.626* (2.14)
Observations	162	162
R^2	0.229	0.132
Adjusted R^2	0.215	0.115

[‡] The number of ‡ indicates the number of lags for aggregate short interest.

Table 5: Effects of Aggregate Short Interest at Various Lags on Cyclical Changes in GDP with Select Controls

Each column in this table reports the results of OLS regressions using cyclical changes in GDP as the dependent variable. The first regression investigates the effects of the aggregate short interest at the lag of 1 quarter with select controls. The second regression investigates the effects of the aggregate short interest at the lag of 2 quarters with select controls. The third regression investigates the aggregate short interest at the lag of 3 quarters with select controls. And the fourth regression investigates the effects of the aggregate short interest at the lag of 4 quarters with select controls. All regressors except for the aggregate short interest at the lag of 4 quarters are significant at the 5% level. The t statistics on the aggregate short interest consistently decreases with increasing lags. The statistical significance for coefficients is indicated by * for significance at the 5% level, ** for significance at the 1% level and *** for significance at the 0.1% level and t statistics are in parentheses.

	(1) ΔGDP with Hodrick-Prescott	(2) ΔGDP with Hodrick-Prescott	(3) ΔGDP with Hodrick-Prescott	(4) ΔGDP with Hodrick-Prescott
Short Interest [‡]	-0.233** (-3.32)			
Short Interest ^{‡‡}		-0.220** (-3.07)		
Short Interest ^{‡‡‡}			-0.165* (-2.29)	
Short Interest ^{‡‡‡‡}				-0.0997 (-1.40)
Federal Funds Rate	0.232*** (5.80)	0.228*** (5.53)	0.229*** (5.15)	0.239*** (4.93)
Treasury 10-Year	-0.247*** (-4.49)	-0.244*** (-4.16)	-0.253*** (-3.99)	-0.274*** (-3.97)
Constant	1.118*** (4.07)	1.077*** (4.10)	0.960*** (3.72)	0.831** (3.13)
Observations	162	161	160	159

[‡] The number of ‡ indicates the number of lags for aggregate short interest.

Table 6: Predictability of Aggregate Short Interest for Negative Cyclical Changes in GDP with Select Controls

Each column in this table reports the results of logit regressions using a binary variable that indicates negative cyclical changes in GDP as the dependent variable. The dependent variable is one if the cyclical changes in GDP are negative. The first regression investigates the predictability of the aggregate short interest at the lag of 1 quarter with select controls. The second regression investigates the predictability of the aggregate short interest at the lag of 2 quarters with select controls. The third regression investigates the predictability of the aggregate short interest at the lag of 3 quarters with select controls. And the fourth regression investigates the predictability of the aggregate short interest at the lag of 4 quarters with select controls. All regressors are significant at the 5% level. The statistical significance for coefficients is indicated by * for significance at the 5% level, ** for significance at the 1% level and *** for significance at the 0.1% level and t statistics are in parentheses.

	(1) - Δ GDP with Hodrick-Prescott	(2) - Δ GDP with Hodrick-Prescott	(3) - Δ GDP with Hodrick-Prescott	(4) - Δ GDP with Hodrick-Prescott
Short Interest [‡]	0.876** (3.24)			
Short Interest ^{‡‡}		0.917*** (3.44)		
Short Interest ^{‡‡‡}			0.738** (2.83)	
Short Interest ^{‡‡‡‡}				0.510* (2.42)
Federal Funds Rate	-0.500*** (-3.52)	-0.477*** (-3.35)	-0.445** (-3.17)	-0.423** (-2.91)
Treasury 10-Year	0.440** (2.73)	0.410* (2.48)	0.402* (2.43)	0.408* (2.26)
Constant	-3.079*** (-4.09)	-3.131*** (-4.24)	-2.679*** (-3.63)	-2.107** (-3.14)
Observations	162	161	160	159

[‡] The number of ‡ indicates the number of lags for aggregate short interest.

Table 7: Predictability of Aggregate Short Interest for Recessions as defined by the NBER with Select Controls

Each column in this table reports the results of logit regressions using a binary variable that indicates recessions as defined by the NBER. The dependent variable is one during the NBER-defined recessions. The first regression investigates the predictability of the contemporaneous aggregate short interest with select controls. The second regression investigates the predictability of the aggregate short interest at the lag of 1 quarter with select controls. The statistical significance for coefficients is indicated by * for significance at the 5% level, ** for significance at the 1% level and *** for significance at the 0.1% level and t statistics are in parentheses.

	(1)	(2)
	Indicator for NBER Recession	Indicator for NBER Recession
Short Interest	0.443* (2.17)	
Short Interest [‡]		0.265 (1.32)
Constant	-3.047*** (-4.01)	-2.416*** (-3.33)
Observations	163	162

[‡] The number of [‡] indicates the number of lags for aggregate short interest.

Table 8: Effects of Aggregate Short Interest at Various Lags on Cyclical Changes in GDP

Each column in this table reports the results of OLS regressions using cyclical changes in GDP as the dependent variable. The first regression investigates the effects of the aggregate short interest at the lag of 1 quarter. The second regression investigates the effects of the aggregate short interest at the lag of 2 quarters. The third regression investigates the aggregate short interest at the lag of 3 quarters. And the fourth regression investigates the effects of the aggregate short interest at the lag of 4 quarters. All regressors are significant at the 5% level. The t statistics on the aggregate short interest decreases with increasing lags. The statistical significance for coefficients is indicated by * for significance at the 5% level, ** for significance at the 1% level and *** for significance at the 0.1% level and t statistics are in parentheses.

	(1) Δ GDP with Hodrick-Prescott	(2) Δ GDP with Hodrick-Prescott	(3) Δ GDP with Hodrick-Prescott	(4) Δ GDP with Hodrick-Prescott
Short Interest [‡]	-0.229*** (-3.47)			
Short Interest ^{‡‡}		-0.229*** (-3.60)		
Short Interest ^{‡‡‡}			-0.198** (-3.20)	
Short Interest ^{‡‡‡‡}				-0.148* (-2.37)
Constant	0.741** (2.98)	0.738** (3.00)	0.632* (2.57)	0.467 (1.84)
Observations	162	161	160	159

[‡] The number of ‡ indicates the number of lags for aggregate short interest.

Table 9: Results with Different Trend-Cycle Decomposition Filters

Each column in this table reports the results of OLS regressions using cyclical changes in GDP as the dependent variable. However, the decomposition methods used to obtain cyclical changes in GDP is different for each column. The first dependent variable is obtained from the Hodrick-Prescott filter. The second dependent variable is obtained from the Butterworth filter. The third dependent variable is obtained from the Christiano-Fitzgerald filter. And the fourth dependent variable is obtained from the Baxter-King filter. All regressors are significant at the 5% level. The significance on the aggregate short interest is not unique to the use of the Hodrick-Prescott filter. The statistical significance for coefficients is indicated by * for significance at the 5% level, ** for significance at the 1% level and *** for significance at the 0.1% level and t statistics are in parentheses.

	(1) Δ GDP with Hodrick-Prescott	(2) Δ GDP with Butterworth	(3) Δ GDP with Christiano-Fitzgerald	(4) Δ GDP with Baxter-King
Short Interest [‡]	-0.233** (-3.32)	-0.197** (-3.29)	-0.260*** (-3.87)	-0.222* (-2.53)
Federal Funds Rate	0.232*** (5.80)	0.175*** (5.42)	0.109** (2.78)	0.235*** (4.70)
Treasury 10-Year	-0.247*** (-4.49)	-0.178*** (-3.83)	-0.0974 (-1.71)	-0.262*** (-3.92)
Constant	1.118*** (4.07)	0.856*** (3.69)	0.892** (3.17)	1.165*** (3.43)
Observations	162	162	162	139

[‡] The number of ‡ indicates the number of lags for aggregate short interest.

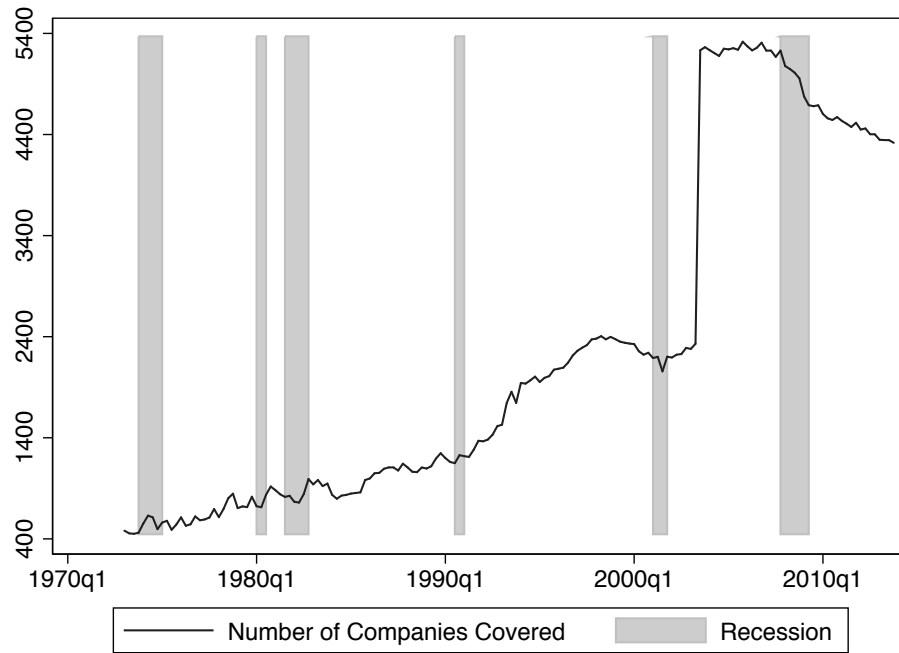


Figure 1: Coverage of Short Interest Data

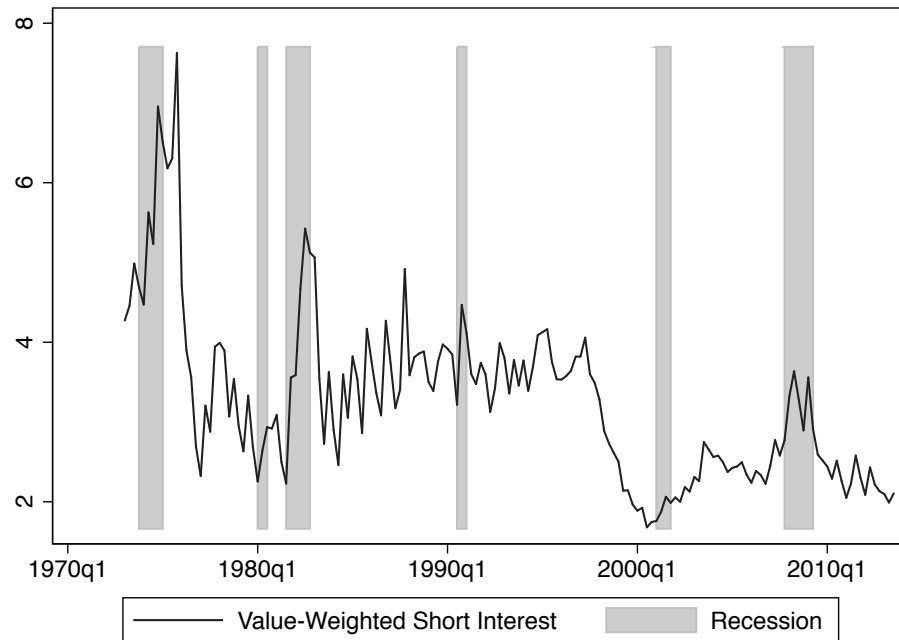


Figure 2: Time Variation of Aggregate Short Interest

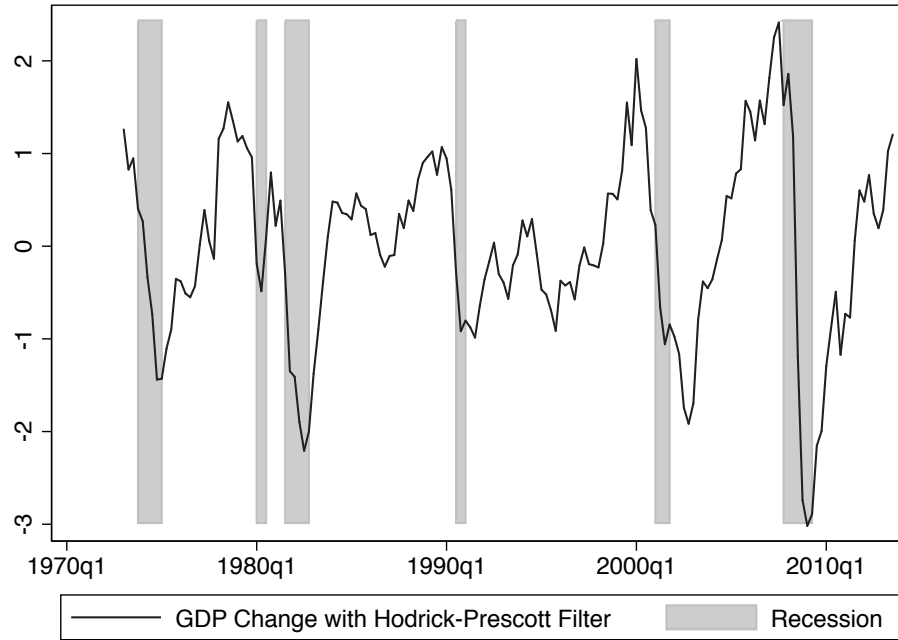


Figure 3: Time Variation of Cyclical Changes in GDP

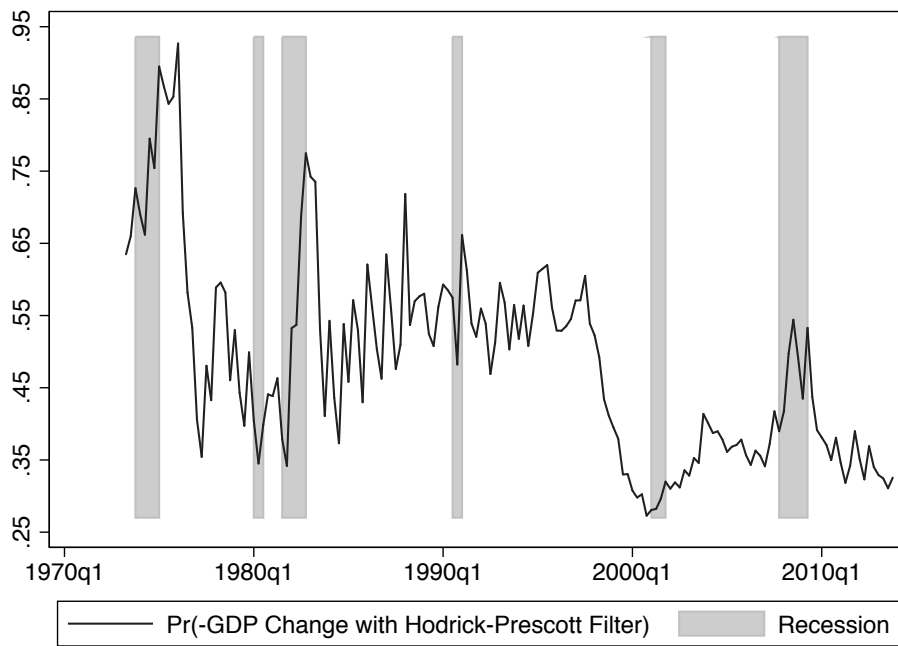


Figure 4: Predictability of Aggregate Short Interest at One Quarter Lag

References

- Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short Interest, Institutional Ownership, and Stock Returns, *Journal of Financial Economics* 78, 243-276.
- Backus, David K., and Patrick J. Kehoe, 1992, International Evidence on the Historical Properties of Business Cycles, *American Economic Review* 82, 864-888.
- Blackburn, Keith, and Morten O. Ravn, 1992, Business Cycles in the U.K.: Facts and Fictions, *Economica* 59, 383-401.
- Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2012, Hedge Fund Stock Trading in the Financial Crisis of 2007-2009, *Review of Financial Studies* 25, 1-54.
- Boehmer, Ekkehart, Zsuzsa R. Huszar, and Bradford D. Jordan, 2010, The Good News in Short Interest, *Journal of Financial Economics* 96, 80-97.
- Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2013, Shackling Short Sellers: The 2008 Shorting Ban, *Review of Financial Studies* 26, 1363-1400.
- Brandner, Peter, and Klaus Neusser, 1992, Business Cycles in Open Economies: Stylized Facts for Austria and Germany, *Weltwirtschaftliches Archiv* 128, 67-87.
- Curtis, Asher, Neil L. Fargher, 2013, Does Short-Selling Amplify Price Declines or Align Stocks with Their Fundamental Values?, *Management Science*, forthcoming.
- Danthine, Jean-Pierre, and John B. Donaldson, 1993, Methodological and Empirical Issues in Real Business Cycle Theory, *European Economic Review* 37, 1-35.
- Danthine, Jean-Pierre, and Michael Girardin, 1989, Business Cycles in Switzerland: A Comparative Study, *European Economic Review* 33, 31-50.
- Fiorito, Ricardo, and Tryphon Kollintzas, 1994, Stylized Facts of Business Cycles in the G7 from a Real Business Cycles Perspective, *European Economic Review* 38, 235-269.
- Griffin, John M., Jeffrey H. Harris, Tao Shu, and Selim Topaloglu, 2011, Who Drove and Burst the Tech Bubble?, *Journal of Finance* 66, 1251-1290.
- Harvey, Andrew C., and A. Jaeger, 1993, Detrending, Stylized Facts and the Business Cycle, *Journal of Applied Econometrics* 8, 231-247.
- Hodrick, Robert J., and Edward C. Prescott, 1997, Postwar U.S. Business Cycles: An Empirical Investigation, *Journal of Money, Credit and Banking* 29, 1-16.

- Kydland, Finn E., and Edward C. Prescott, 1982, Time to Build and Aggregate Fluctuations, *Econometrica* 50, 1345-1370.
- Lamont, Owen A., and Jeremy C. Stein, 2004, Aggregate Short Interest and Market Valuations, *American Economic Review Papers and Proceedings* 94, 29-32.
- Ravn, Morten O., and Harald Uhlig, 2002, On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations, *Review of Economics and Statistics* 84, 371-380.